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Mishra et al.

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(54) MESSAGE ORIENTED MIDDLEWARE CLUSTER SYNCHRONIZATION

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(51) **Int. Cl.**

G06F 9/54	(2006.01)
G06N 20/00	(2019.01)

(52) **U.S. Cl.**
CPC ***G06F 9/546*** (2013.01); ***G06N 20/00*** (2019.01)

(58) **Field of Classification Search**
CPC G06F 9/546; G06N 20/00
See application file for complete search history.

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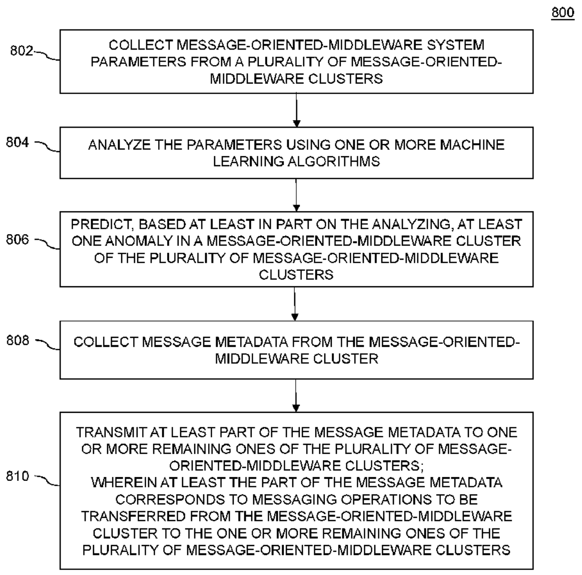
(57) **ABSTRACT**

A method comprises collecting message-oriented-middleware system parameters from a plurality of message-oriented-middleware clusters, analyzing the parameters using one or more machine learning algorithms, and predicting, based at least in part on the analyzing, at least one anomaly in a message-oriented-middleware cluster of the plurality of message-oriented-middleware clusters. In the method, message metadata is collected from the message-oriented-middleware cluster, and at least part of the message metadata is transmitted to one or more remaining ones of the plurality of message-oriented-middleware clusters. At least the part of the message metadata corresponds to messaging operations to be transferred from the message-oriented-middleware cluster to the one or more remaining ones of the plurality of message-oriented-middleware clusters.

20 Claims, 12 Drawing Sheets


800
802
COLLECT MESSAGE-ORIENTED-MIDDLEWARE SYSTEM PARAMETERS FROM A PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS
804
ANALYZE THE PARAMETERS USING ONE OR MORE MACHINE LEARNING ALGORITHMS
806
PREDICT, BASED AT LEAST IN PART ON THE ANALYZING, AT LEAST ONE ANOMALY IN A MESSAGE-ORIENTED-MIDDLEWARE CLUSTER OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS
808
COLLECT MESSAGE METADATA FROM THE MESSAGE-ORIENTED-MIDDLEWARE CLUSTER
810
TRANSMIT AT LEAST PART OF THE MESSAGE METADATA TO ONE OR MORE REMAINING ONES OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS; WHEREIN AT LEAST THE PART OF THE MESSAGE METADATA CORRESPONDS TO MESSAGING OPERATIONS TO BE TRANSFERRED FROM THE MESSAGE-ORIENTED-MIDDLEWARE CLUSTER TO THE ONE OR MORE REMAINING ONES OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS

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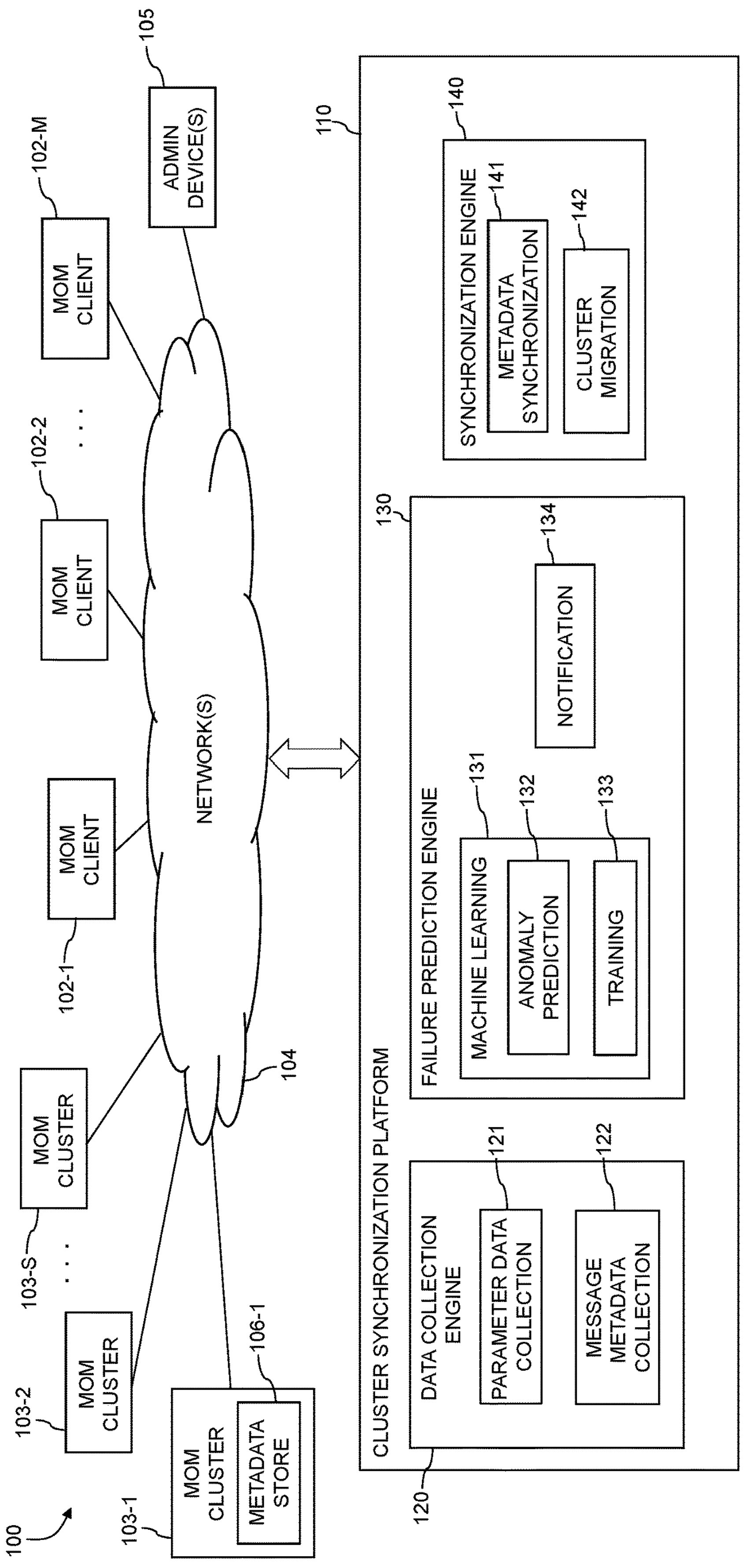

100
MOM CLUSTER
METADATA STORE
103-1
106-1
MOM CLUSTER
103-2
. . .
MOM CLUSTER
103-S
MOM CLIENT
102-1
MOM CLIENT
102-2
. . .
MOM CLIENT
102-M
ADMIN DEVICE(S)
105
NETWORK(S)
104
110
CLUSTER SYNCHRONIZATION PLATFORM
120
DATA COLLECTION ENGINE
121
PARAMETER DATA COLLECTION
122
MESSAGE METADATA COLLECTION
130
FAILURE PREDICTION ENGINE
131
MACHINE LEARNING
132
ANOMALY PREDICTION
133
TRAINING
134
NOTIFICATION
140
SYNCHRONIZATION ENGINE
141
METADATA SYNCHRONIZATION
142
CLUSTER MIGRATION

FIG. 1

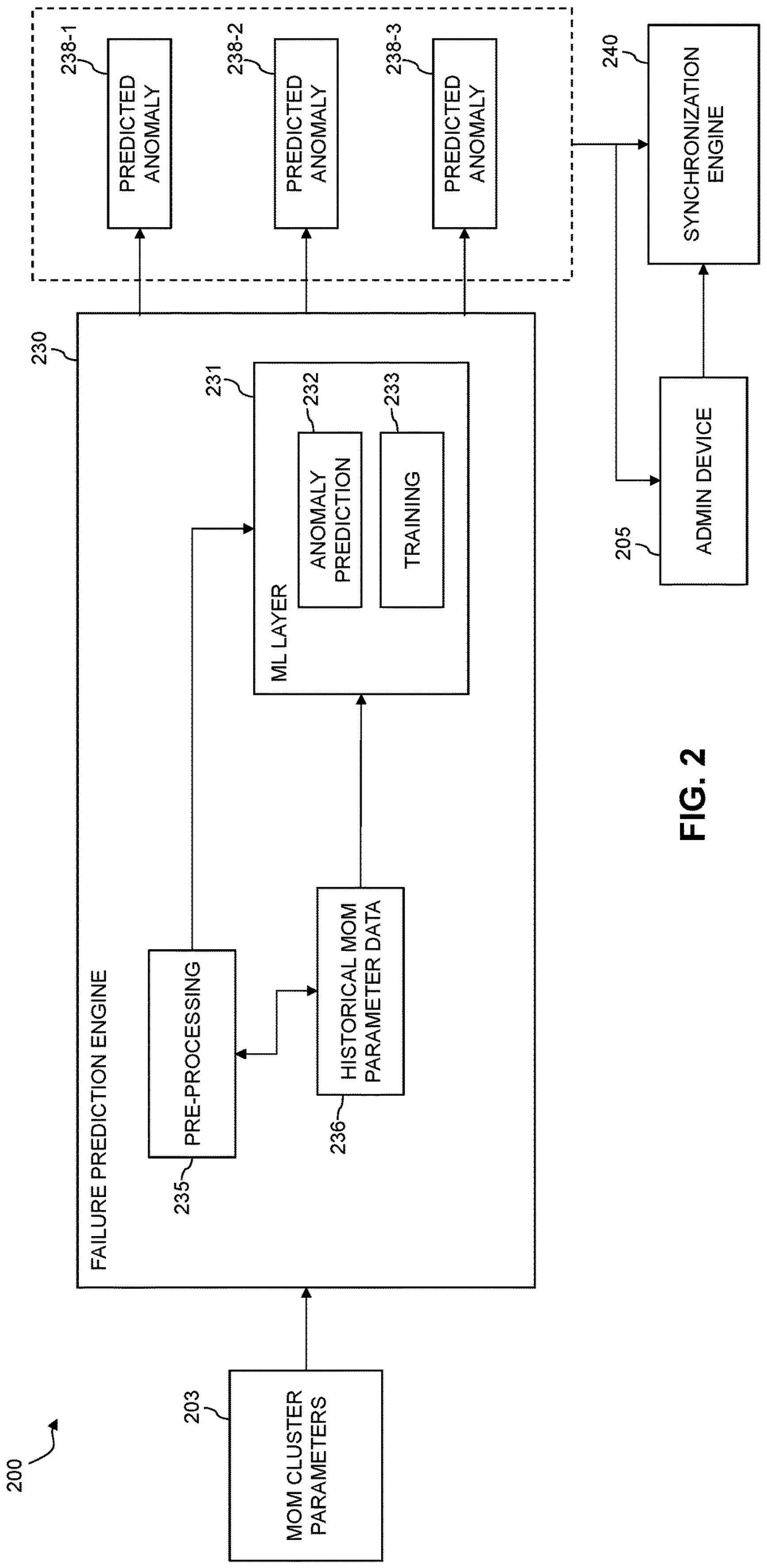

200
203
MOM CLUSTER PARAMETERS
230
FAILURE PREDICTION ENGINE
235
PRE-PROCESSING
236
HISTORICAL MOM PARAMETER DATA
231
ML LAYER
232
ANOMALY PREDICTION
233
TRAINING
238-1
PREDICTED ANOMALY
238-2
PREDICTED ANOMALY
238-3
PREDICTED ANOMALY
240
SYNCHRONIZATION ENGINE
205
ADMIN DEVICE

FIG. 2

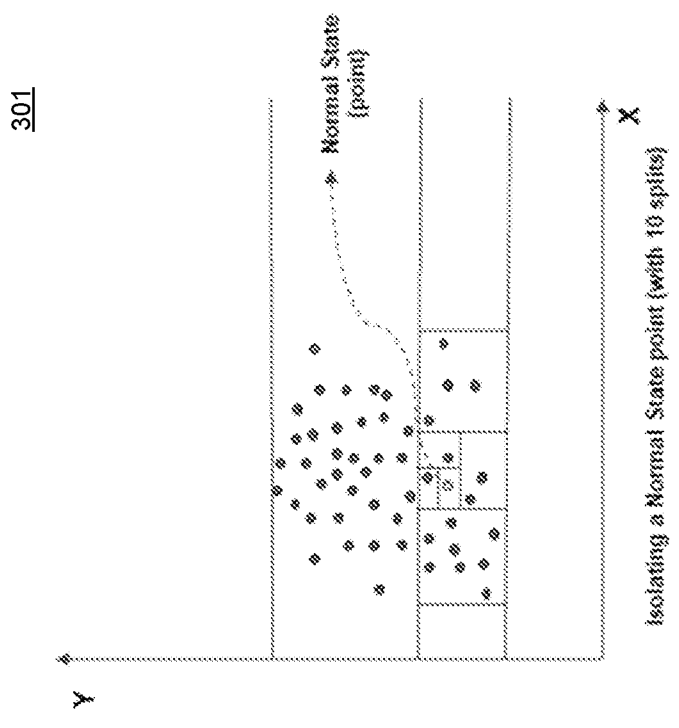

301
Normal State (point)
Y
X
Isolating a Normal State point (with 10 splits)

FIG. 3A

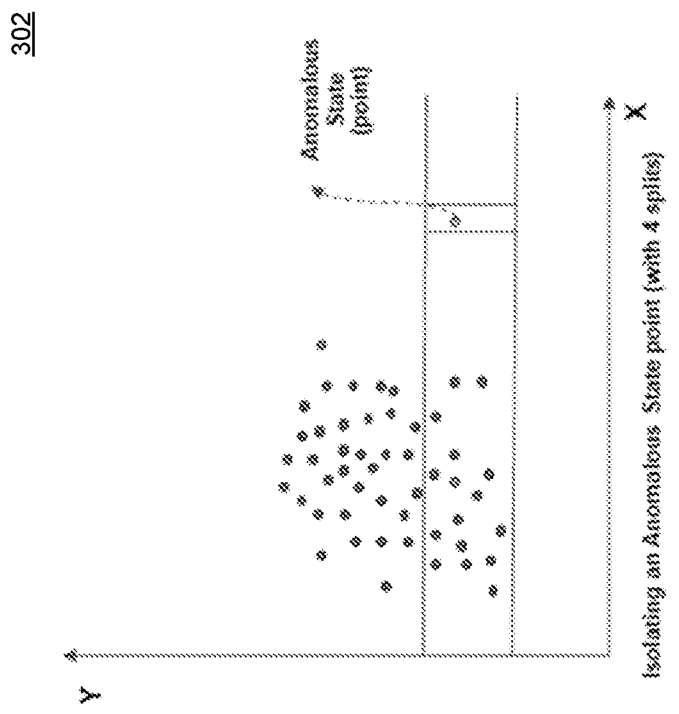
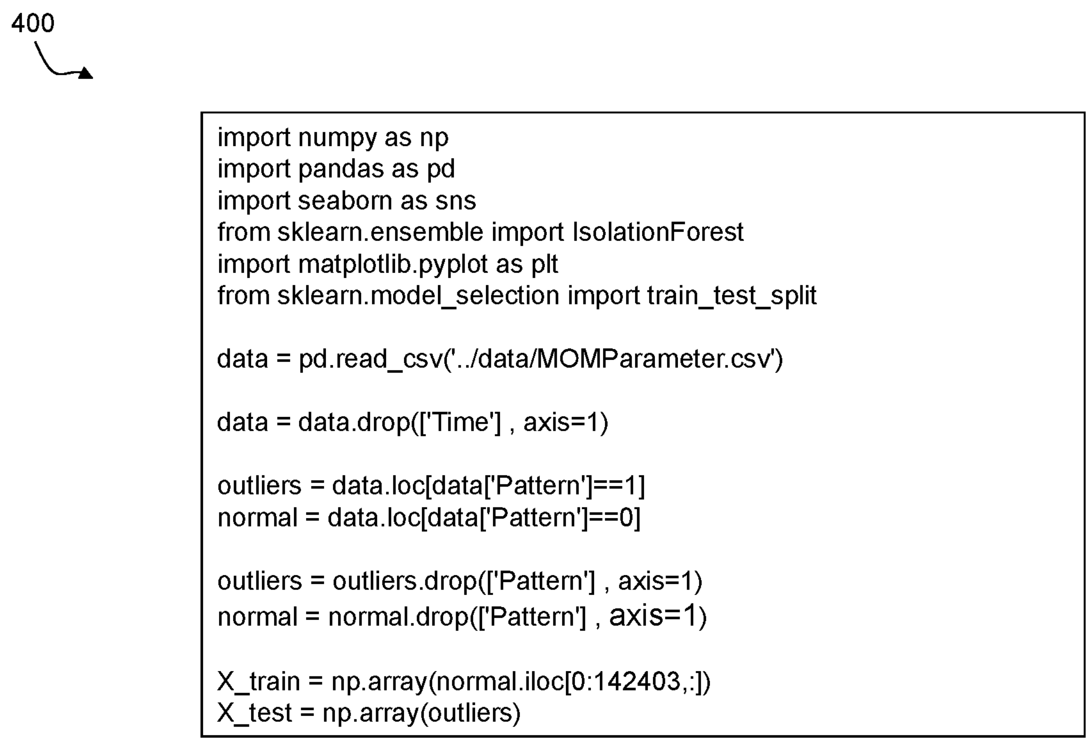

302
Anomalous State (point)
Y
X
Isolating an Anomalous State point (with 4 splits)

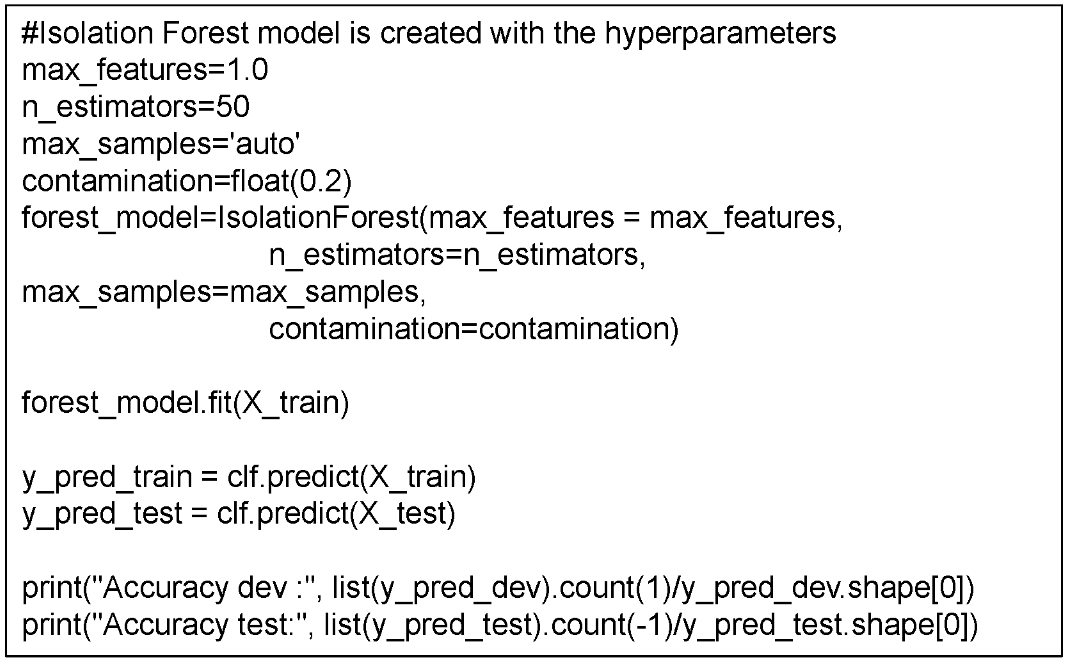
FIG. 3B



```
import numpy as np
import pandas as pd
import seaborn as sns
from sklearn.ensemble import IsolationForest
import matplotlib.pyplot as plt
from sklearn.model_selection import train_test_split

data = pd.read_csv('../data/MOMParameter.csv')

data = data.drop(['Time'] , axis=1)

outliers = data.loc[data['Pattern']==1]
normal = data.loc[data['Pattern']==0]

outliers = outliers.drop(['Pattern'] , axis=1)
normal = normal.drop(['Pattern'] , axis=1)

X_train = np.array(normal.iloc[0:142403,:])
X_test = np.array(outliers)
```

FIG. 4

400 (cont'd)



```
#Isolation Forest model is created with the hyperparameters
max_features=1.0
n_estimators=50
max_samples='auto'
contamination=float(0.2)
forest_model=IsolationForest(max_features = max_features,
                        n_estimators=n_estimators,
max_samples=max_samples,
                        contamination=contamination)

forest_model.fit(X_train)

y_pred_train = clf.predict(X_train)
y_pred_test = clf.predict(X_test)

print("Accuracy dev :", list(y_pred_dev).count(1)/y_pred_dev.shape[0])
print("Accuracy test:", list(y_pred_test).count(-1)/y_pred_test.shape[0])
```

FIG. 4 (cont'd)

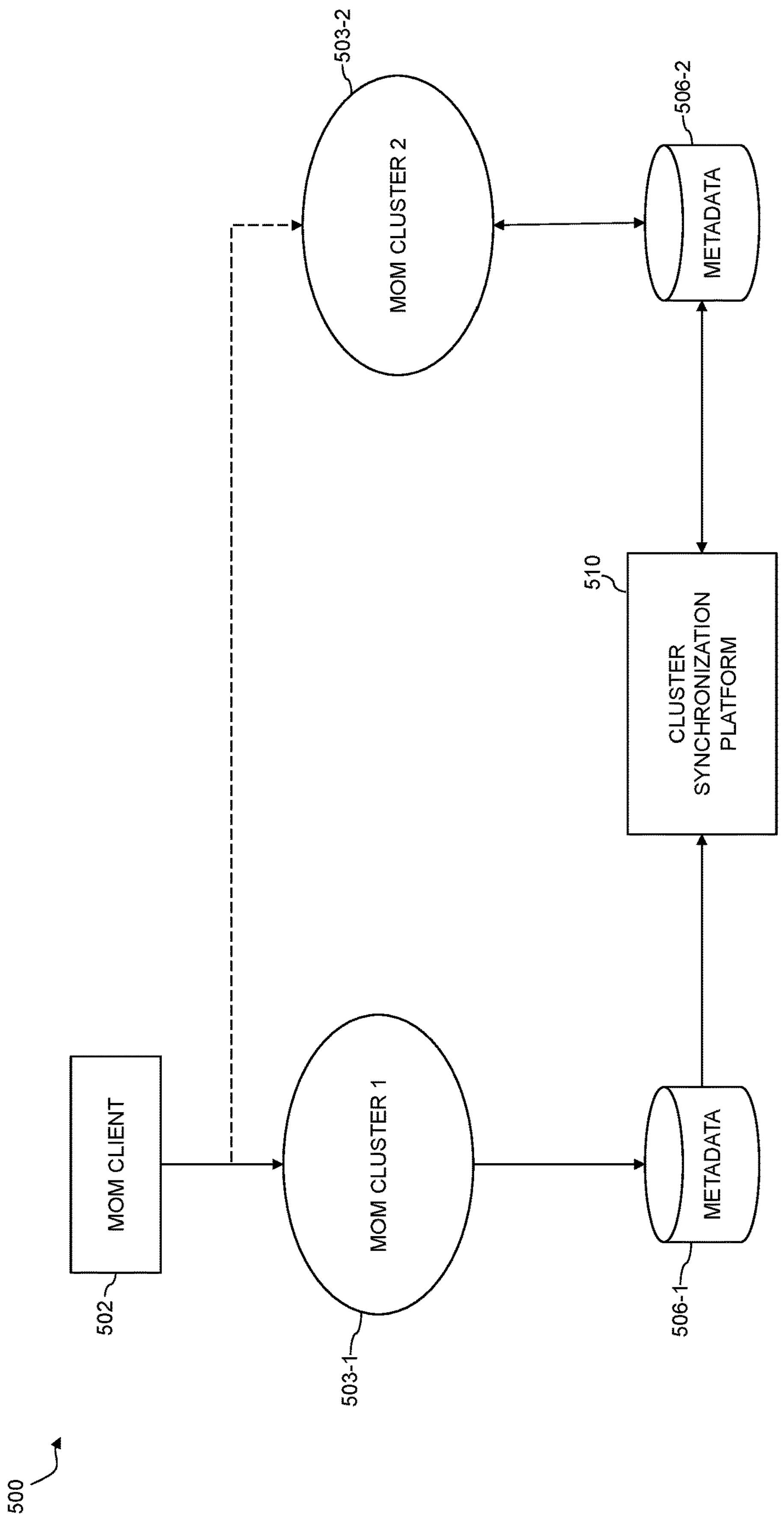

500
MOM CLIENT
502
MOM CLUSTER 1
503-1
METADATA
506-1
CLUSTER SYNCHRONIZATION PLATFORM
510
MOM CLUSTER 2
503-2
METADATA
506-2

FIG. 5

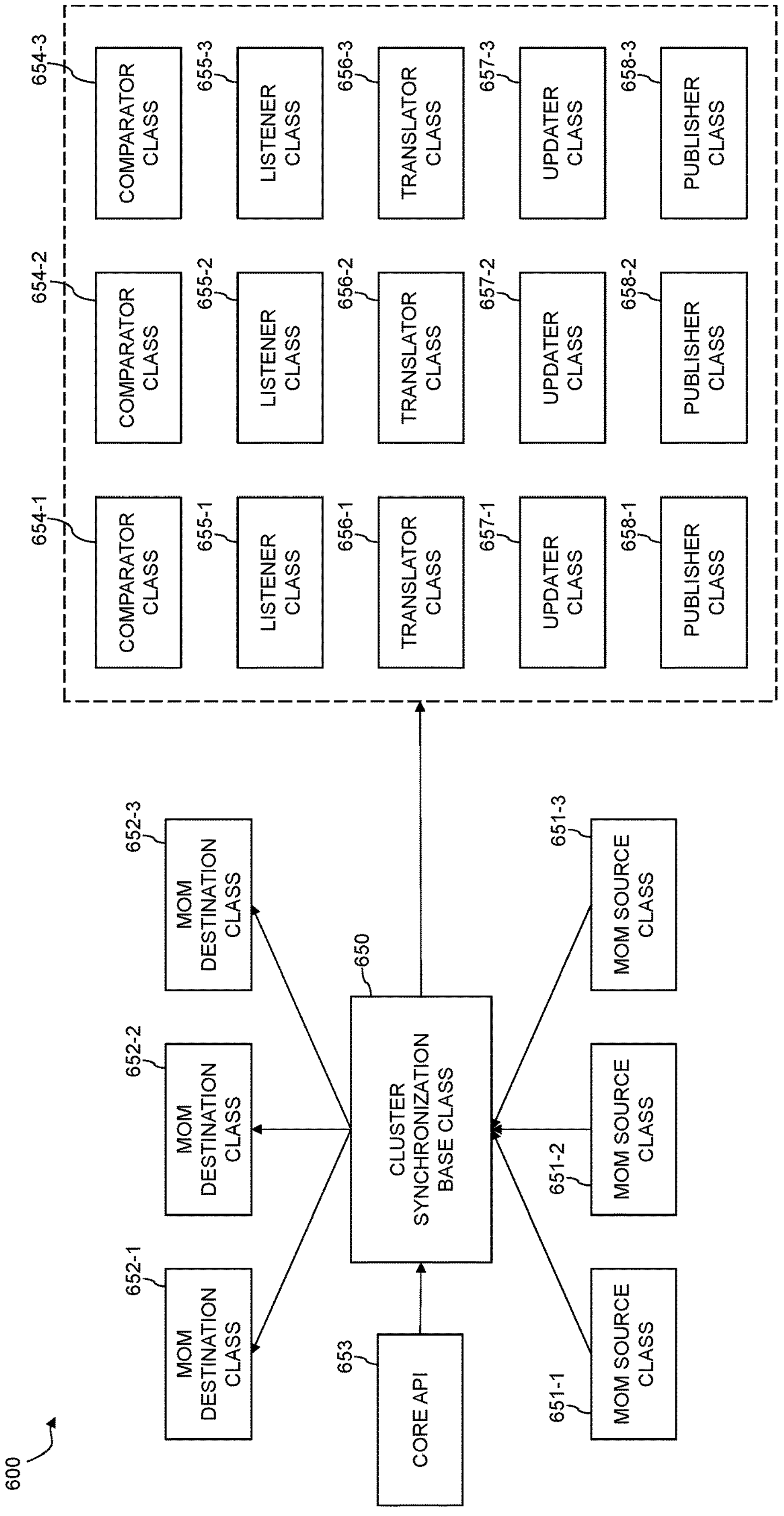

600
MOM DESTINATION CLASS
652-1
MOM DESTINATION CLASS
652-2
MOM DESTINATION CLASS
652-3
CORE API
653
CLUSTER SYNCHRONIZATION BASE CLASS
650
MOM SOURCE CLASS
651-1
MOM SOURCE CLASS
651-2
MOM SOURCE CLASS
651-3
COMPARATOR CLASS
654-1
COMPARATOR CLASS
654-2
COMPARATOR CLASS
654-3
LISTENER CLASS
655-1
LISTENER CLASS
655-2
LISTENER CLASS
655-3
TRANSLATOR CLASS
656-1
TRANSLATOR CLASS
656-2
TRANSLATOR CLASS
656-3
UPDATER CLASS
657-1
UPDATER CLASS
657-2
UPDATER CLASS
657-3
PUBLISHER CLASS
658-1
PUBLISHER CLASS
658-2
PUBLISHER CLASS
658-3

FIG. 6

700

```
public void momConnectQ(String host1, String qMgrName1, String channel1, String
queueName1, int port1, boolean switchflg,
                                                String host2, String qMgrName2,
String channel2, String queueName2, int port2) throws MQException {

            try
                        {
                        if (switchflg){

            momSetProperties(host1,qMgrName1,channel1,queueName1, port1);

                        momBrowseFirstMsg(qMgr1, qMgrName1, localQueue,
queueName1);
                        } else          {

            momSetProperties(host2,qMgrName2,channel2,queueName2, port2);

                        momBrowseFirstMsg(qMgr2, qMgrName2, localQueue,
queueName2);
                        }
```

FIG. 7

700 (Cont'd)

```
} catch (MQException ex)  {
                                        System.out.println(
                                                     "An MQSeries error occured
mqConnectQ : Completion code "
                                                                  +
ex.completionCode
                                                                  + " Reason code "
                                                                  + ex.reasonCode);


                } catch (Exception e) {
                           System.out.println("An unknown exception occured
mqConnectQ :" + e.toString());
                }

             }
```

FIG. 7 (Cont'd)

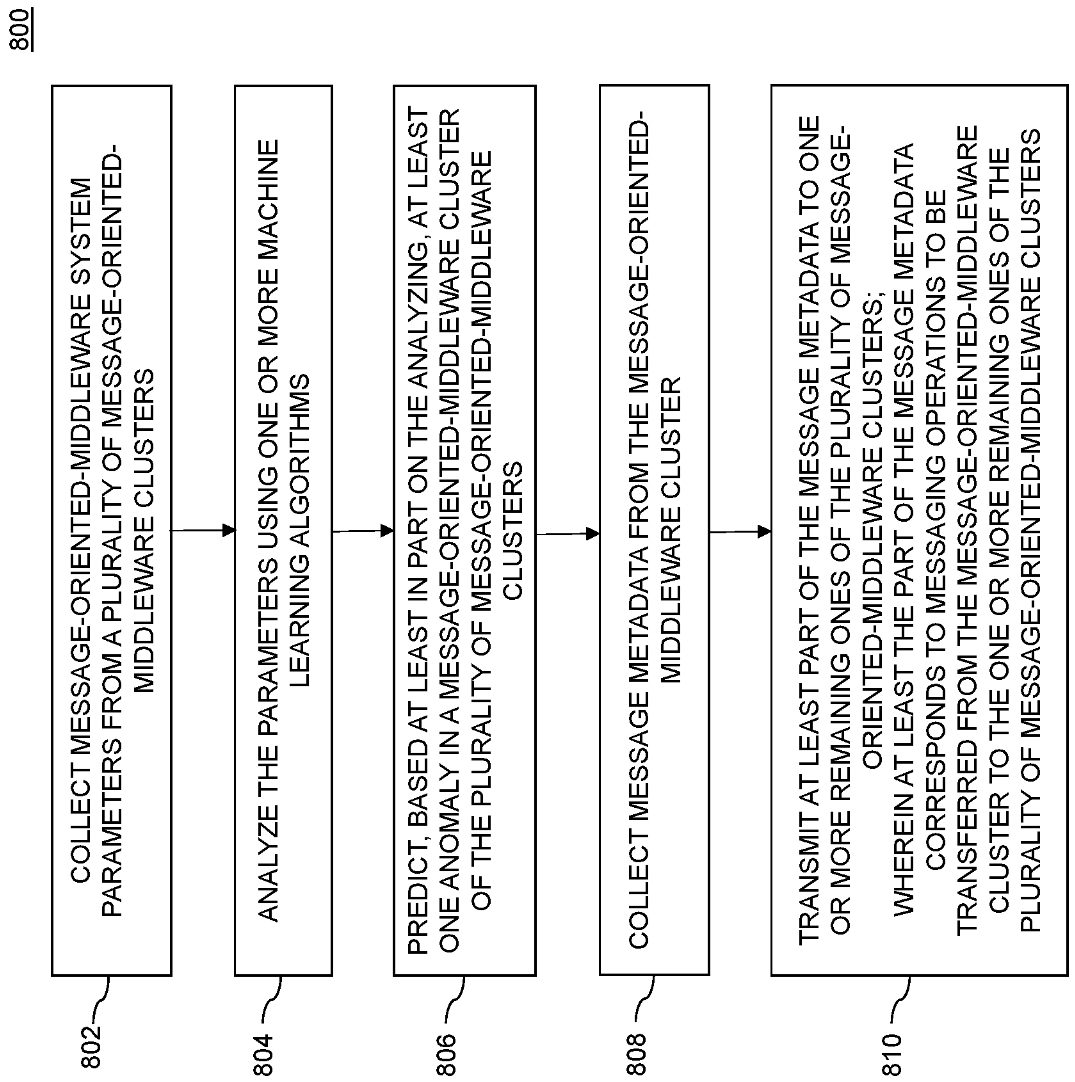

800
802
COLLECT MESSAGE-ORIENTED-MIDDLEWARE SYSTEM PARAMETERS FROM A PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS
804
ANALYZE THE PARAMETERS USING ONE OR MORE MACHINE LEARNING ALGORITHMS
806
PREDICT, BASED AT LEAST IN PART ON THE ANALYZING, AT LEAST ONE ANOMALY IN A MESSAGE-ORIENTED-MIDDLEWARE CLUSTER OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS
808
COLLECT MESSAGE METADATA FROM THE MESSAGE-ORIENTED-MIDDLEWARE CLUSTER
810
TRANSMIT AT LEAST PART OF THE MESSAGE METADATA TO ONE OR MORE REMAINING ONES OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS;
WHEREIN AT LEAST THE PART OF THE MESSAGE METADATA CORRESPONDS TO MESSAGING OPERATIONS TO BE TRANSFERRED FROM THE MESSAGE-ORIENTED-MIDDLEWARE CLUSTER TO THE ONE OR MORE REMAINING ONES OF THE PLURALITY OF MESSAGE-ORIENTED-MIDDLEWARE CLUSTERS

FIG. 8

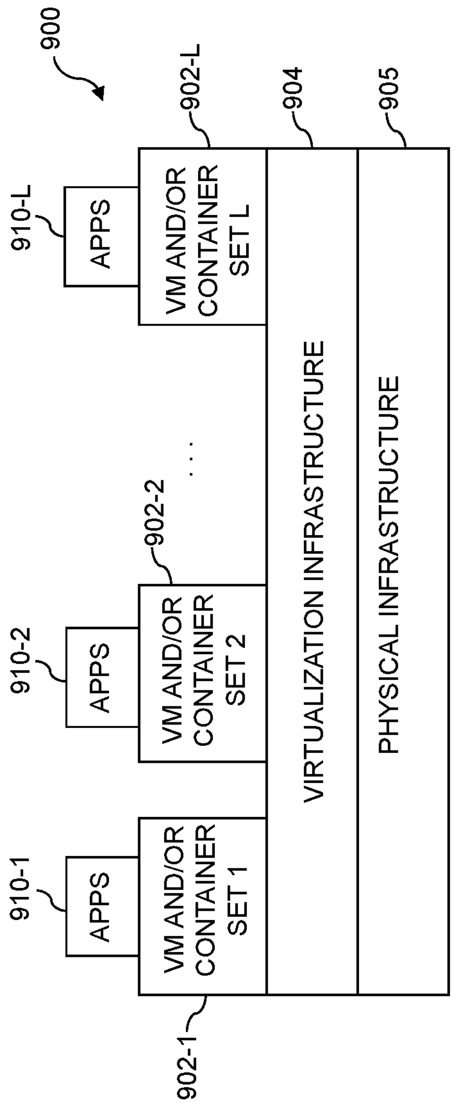

900
910-1
APPS
VM AND/OR CONTAINER SET 1
902-1
910-2
APPS
VM AND/OR CONTAINER SET 2
902-2
. . .
910-L
APPS
VM AND/OR CONTAINER SET L
902-L
VIRTUALIZATION INFRASTRUCTURE
904
PHYSICAL INFRASTRUCTURE
905

FIG. 9

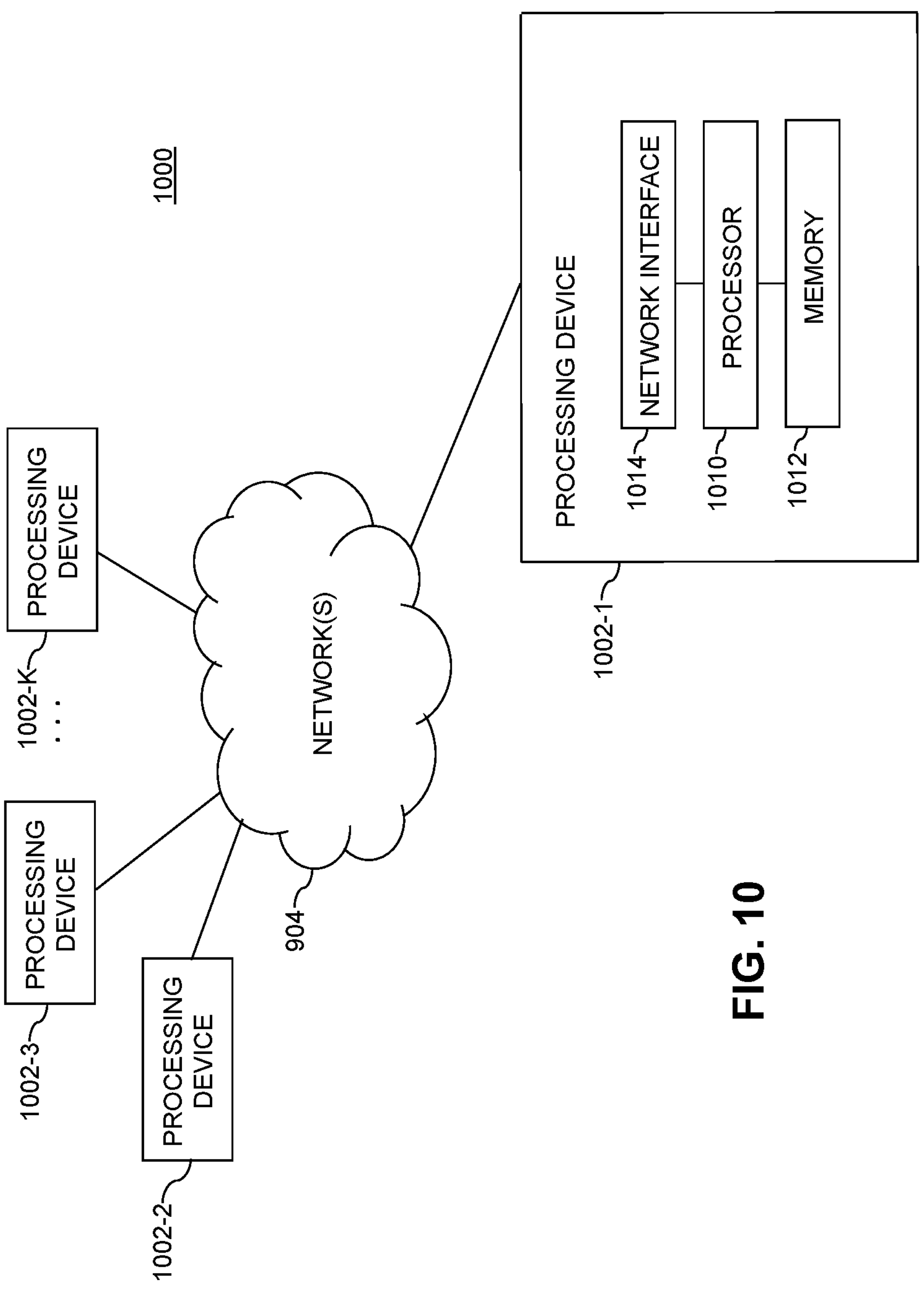

1000
PROCESSING DEVICE
1002-K
...
PROCESSING DEVICE
1002-3
PROCESSING DEVICE
1002-2
NETWORK(S)
904
PROCESSING DEVICE
NETWORK INTERFACE
PROCESSOR
MEMORY
1014
1010
1012
1002-1

FIG. 10

MESSAGE ORIENTED MIDDLEWARE CLUSTER SYNCHRONIZATION

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FIELD

The field relates generally to information processing systems, and more particularly to a framework for synchronizing message-oriented-middleware clusters.

BACKGROUND

Message delivery is crucial to the success of enterprise information technology (IT) system operations. In some enterprises, for example, hundreds of mission critical applications use a messaging infrastructure to process hundreds of million messages each day. In addition, enterprises may utilize a variety of different message-oriented-middleware (MOM) products to deliver their messages.

Under conventional approaches, when servers fail and MOM clients are required to switch from one MOM server group to another MOM server group, the new MOM server group lacks information corresponding to previously committed messages. As a result, message processing is restarted from the beginning (e.g., a first message) and not where message processing left off prior to the failure. This leads to duplicity and seriously impacts scalability and operation management, thereby hindering active-active architectures.

SUMMARY

Embodiments provide a cluster synchronization platform in an information processing system.

For example, in one embodiment, a method comprises collecting message-oriented-middleware system parameters from a plurality of message-oriented-middleware clusters, analyzing the parameters using one or more machine learning algorithms, and predicting, based at least in part on the analyzing, at least one anomaly in a message-oriented-middleware cluster of the plurality of message-oriented-middleware clusters. In the method, message metadata is collected from the message-oriented-middleware cluster, and at least part of the message metadata is transmitted to one or more remaining ones of the plurality of message-oriented-middleware clusters. At least the part of the message metadata corresponds to messaging operations to be transferred from the message-oriented-middleware cluster to the one or more remaining ones of the plurality of message-oriented-middleware clusters.

Further illustrative embodiments are provided in the form of a non-transitory computer-readable storage medium having embodied therein executable program code that when executed by a processor causes the processor to perform the above steps. Still further illustrative embodiments comprise an apparatus with a processor and a memory configured to perform the above steps.

These and other features and advantages of embodiments described herein will become more apparent from the accompanying drawings and the following detailed description.

BRIEF DESCRIPTION OF THE DRAWINGS

FIG. **1** depicts an information processing system with a cluster synchronization platform in an illustrative embodiment.

FIG. **2** depicts an operational flow for anomaly prediction in an illustrative embodiment.

FIG. **3**A depicts a plot illustrating isolation of a normal state point in an illustrative embodiment.

FIG. **3**B depicts a plot illustrating isolation of an anomalous state point in an illustrative embodiment.

FIG. **4** depicts example pseudocode for anomaly prediction in an illustrative embodiment.

FIG. **5** depicts an operational flow for cluster migration in an illustrative embodiment.

FIG. **6** depicts a class diagram for implementing cluster synchronization in an illustrative embodiment.

FIG. **7** depicts example pseudocode for cluster migration in an illustrative embodiment.

FIG. **8** depicts a process for cluster synchronization according to an illustrative embodiment.

FIGS. **9** and **10** show examples of processing platforms that may be utilized to implement at least a portion of an information processing system according to illustrative embodiments.

DETAILED DESCRIPTION

Illustrative embodiments will be described herein with reference to exemplary information processing systems and associated computers, servers, storage devices and other processing devices. It is to be appreciated, however, that embodiments are not restricted to use with the particular illustrative system and device configurations shown. Accordingly, the term "information processing system" as used herein is intended to be broadly construed, so as to encompass, for example, processing systems comprising cloud computing and storage systems, as well as other types of processing systems comprising various combinations of physical and virtual processing resources. An information processing system may therefore comprise, for example, at least one data center or other type of cloud-based system that includes one or more clouds hosting tenants that access cloud resources. Such systems are considered examples of what are more generally referred to herein as cloud-based computing environments. Some cloud infrastructures are within the exclusive control and management of a given enterprise, and therefore are considered "private clouds." The term "enterprise" as used herein is intended to be broadly construed, and may comprise, for example, one or more businesses, one or more corporations or any other one or more entities, groups, or organizations. An "entity" as illustratively used herein may be a person or system. On the other hand, cloud infrastructures that are used by multiple enterprises, and not necessarily controlled or managed by any of the multiple enterprises but rather respectively controlled and managed by third-party cloud providers, are typically considered "public clouds." Enterprises can choose to host their applications or services on private clouds, public clouds, and/or a combination of private and public clouds (hybrid clouds) with a vast array of computing resources attached to or otherwise a part of the infrastructure. Numerous other types of enterprise computing and storage systems are also encompassed by the term "information processing system" as that term is broadly used herein.

As used herein, "real-time" refers to output within strict time constraints. Real-time output can be understood to be instantaneous or on the order of milliseconds or microseconds. Real-time output can occur when the connections with a network are continuous and a user device receives messages without any significant time delay. Of course, it should be understood that depending on the particular temporal nature of the system in which an embodiment is implemented, other appropriate timescales that provide at least contemporaneous performance and output can be achieved.

As used herein, "application programming interface (API)" or "interface" refers to a set of subroutine definitions, protocols, and/or tools for building software. Generally, an API defines communication between software components. APIs permit programmers to write software applications consistent with an operating environment or website.

As used herein, the term "middleware" is to be broadly construed to refer to software that links different applications. Some examples of middleware are products that establish connections between web servers and database systems and connections between message producers and consumers.

Message-oriented-middleware or "MOM" providers or systems include architectures with, for example, APIs and administrative tools to route and deliver messages. In an embodiment, the MOM providers or systems respectively run on different operating systems and/or platforms or different implementations of the same operating system and/or platform. For example, the MOM providers or systems are of different types, and require different functionality or implementations of connectivity/messaging protocols, such as, for example, machine-to-machine (M2M) messaging protocols. In a non-limiting embodiment, M2M protocols can include, but are not necessarily limited to, Message Queuing Telemetry Transport (MQTT), constrained application protocol (CoAP), and/or OMA lightweight machine to machine (LWM2M). Some non-limiting examples of MOM providers are IBM® MQ (International Business Machines Corporation, Armonk, NY), RabbitMQ® (Pivotal Software, Inc., San Francisco, CA), Apache™ ActiveMQ® and Apache™ Kafka® (Apache Software Foundation, Wakefield, MA).

As used herein, the term "cluster" is to be broadly construed to refer to multiple devices, such as, for example, multiple servers (also referred to herein as "nodes"), that work together to deliver services. Nodes of a cluster can be redundant. In one or more embodiments, a MOM provider or system includes a cluster (or multiple clusters) to provide the services of the MOM provider or system. A cluster of a MOM provider or system is referred to herein as a "MOM cluster."

FIG. **1** shows an information processing system **100** configured in accordance with an illustrative embodiment. The information processing system **100** comprises MOM clients **102-1**, **102-2**, . . . **102**-M (collectively "MOM clients **102**"), MOM clusters **103-1**, **103-2**, . . . **103**-S (collectively "MOM clusters **103**"), and one or more administrator devices ("Admin device(s)") **105**. The MOM clients **102**, MOM clusters **103** and administrator devices **105** communicate over a network **104** with a cluster synchronization platform **110**. The MOM clients **102** comprise message producers (also referred to herein as "publishers") and/or message consumers (also referred to herein as "subscribers"). Messages from producer/publisher MOM clients **102** may be pushed to consumer/subscriber MOM clients **102** using one or more MOM clusters **103**. For example, a message can be published by a producer/publisher MOM client **102**, and sent to consumer/subscriber MOM clients **102** that have registered to receive messages for the topic to which the message pertains. In some embodiments, MOM clients **102** receive messages based on a subscription to a certain topic. A MOM cluster **103** or individual server of a MOM system provides the services to push messages with a topic matching a subscription from a publisher MOM client **102** to a subscribed MOM client **102**. Sending a message is referred to as publishing, and registering to receive messages for a topic is referred to as subscribing. If communication between MOM clients **102** is topic-based, a relationship is not required between MOM clients **102** in order for a client to receive a message from another client.

The MOM clients **102**, MOM clusters **103** and administrator devices **105** can comprise, for example, Internet of Things (IoT) devices, desktop, laptop or tablet computers, mobile telephones, or other types of processing devices capable of communicating with the cluster synchronization platform **110** over the network **104**. Such devices are examples of what are more generally referred to herein as "processing devices." Some of these processing devices are also generally referred to herein as "computers." The MOM clients **102**, MOM clusters **103** and administrator devices **105** may also or alternately comprise virtualized computing resources, such as virtual machines (VMs), containers, etc. The MOM clients **102**, MOM clusters **103** and/or administrator devices **105** in some embodiments comprise respective computers associated with a particular company, organization or other enterprise. The variable M and other similar index variables herein such as K, L and S are assumed to be arbitrary positive integers greater than or equal to two.

The terms "user" or "administrator" herein are intended to be broadly construed so as to encompass numerous arrangements of human, hardware, software or firmware entities, as well as combinations of such entities. Cluster synchronization services may be provided for users utilizing one or more machine learning models, although it is to be appreciated that other types of infrastructure arrangements could be used. At least a portion of the available services and functionalities provided by the cluster synchronization platform **110** in some embodiments may be provided under Function-as-a-Service ("FaaS"), Containers-as-a-Service ("CaaS") and/or Platform-as-a-Service ("PaaS") models, including cloud-based FaaS, CaaS and PaaS environments.

Although not explicitly shown in FIG. **1**, one or more input-output devices such as keyboards, displays or other types of input-output devices may be used to support one or more user interfaces to the cluster synchronization platform **110**, as well as to support communication between the cluster synchronization platform **110** and connected devices (e.g., administrator devices **105**) and/or other related systems and devices not explicitly shown.

In some embodiments, the administrator devices **105** are assumed to be associated with repair technicians, system administrators, information technology (IT) managers, software developers, release management personnel or other authorized personnel configured to access and utilize the cluster synchronization platform **110**.

Each of the MOM clusters **103** includes a metadata store, such as, for example, metadata store **106-1** corresponding to MOM cluster **103-1**. Metadata stores for the remaining MOM clusters **103** in FIG. **1** are not shown. The metadata store **106-1** stores message metadata comprising, for example, details of message processing such as, but not necessarily limited to, message offset information, last message read information, last message committed information, timestamps, topic attributes, transaction identifiers and/or details about the protocols, interfaces and channels being used to deliver the messages. The timestamps may comprise, for example, a last message read timestamp and a last message committed timestamp. The transaction identifier may comprise, for example, an identifier of a pending 2-phase commit message.

The message metadata is cluster specific, and respective MOM clusters **103** may not contain the same message metadata as each other. For example, under conventional techniques, a consumer MOM client may be processing a batch of 100 persistent messages, and at the 20^{th} message, a first cluster processing the messages fails due to some problem (e.g., system problems causing a listener port to drop). Under current approaches, a second cluster does not include the metadata corresponding to the information of the already committed messages (e.g., offsets to the logged space). As a result, if operations are switched to the second cluster, message processing will start from a first message instead of the 20^{th} message. Unlike conventional approaches, the embodiments provide a predictive and proactive failover framework for MOM systems, where cluster anomalies are predicted prior to their occurrence and necessary message state metadata is synchronized between primary and failover clusters. As a result, when messaging operations are migrated from a primary MOM cluster to a failover MOM cluster, the failover cluster has the necessary state information so that messaging continues from a point where failover occurred and transactional integrity and quality of service (QoS) are maintained. Alternatively, messaging operations are migrated from a primary MOM cluster to a failover MOM cluster before a failure occurs (i.e., in anticipation of a failure) and due to the synchronization of the metadata, the same result of continuing message operations from a point of the last committed message is achieved when moving operations between MOM clusters **103**.

According to an embodiment, different servers, different MOM platforms and different message channels are associated with respective ones of the MOM clusters **103**, which use different protocols and interfaces. In an illustrative embodiment, the MOM clusters **103** may correspond to different MOM providers (e.g., IBM® MQ, RabbitMQ®, Apache™ ActiveMQ® and Apache™ Kafka®). In another illustrative embodiment, at least some of the MOM clusters **103** may correspond to the same MOM provider.

The cluster synchronization platform **110** in the present embodiment is assumed to be accessible to the MOM clients **102**, MOM clusters **103** and/or administrator devices **105** over the network **104**. The network **104** is assumed to comprise a portion of a global computer network such as the Internet, although other types of networks can be part of the network **104**, including a wide area network (WAN), a local area network (LAN), a satellite network, a telephone or cable network, a cellular network, a wireless network such as a WiFi or WiMAX network, or various portions or combinations of these and other types of networks. The network **104** in some embodiments therefore comprises combinations of multiple different types of networks each comprising processing devices configured to communicate using Internet Protocol (IP) or other related communication protocols.

As a more particular example, some embodiments may utilize one or more high-speed local networks in which

associated processing devices communicate with one another utilizing Peripheral Component Interconnect express (PCIe) cards of those devices, and networking protocols such as InfiniBand, Gigabit Ethernet or Fibre Channel. Numerous alternative networking arrangements are possible in a given embodiment, as will be appreciated by those skilled in the art.

The cluster synchronization platform **110** is configured to detect anomalies, predict any upcoming errors and control the migration of operations to a failover cluster before an actual outage requires reactive error handling. By leveraging machine learning for anomaly detection, the embodiments monitor various system parameters including MOM system metrics. By measuring the normal parameter values, the machine learning model can detect anomalies when the parameter values deviate from the normal values. Based on the identification of one or more anomalies, the cluster synchronization platform **110** can make a decision to switch to a secondary cluster before an outage of the primary cluster occurs. In this way, issues in a primary cluster can be investigated, while messages flow uninterrupted through a secondary cluster.

Referring to FIG. **1**, the cluster synchronization platform **110** includes a data collection engine **120**, a failure prediction engine **130** and a synchronization engine **140**. The data collection engine **120** includes a parameter data collection layer **121** and a message metadata collection layer **122**. The failure prediction engine **130** includes a machine learning layer **131** comprising anomaly prediction and training layers **132** and **133**, and a notification layer **134**. The synchronization engine **140** includes a metadata synchronization layer **141** and a cluster migration layer **142**.

The parameter data collection layer **121** of the data collection engine **120** collects MOM system parameters from the MOM clusters **103**. The system parameters comprise, for example, central processing unit (CPU) utilization parameters (e.g., processing volume, memory utilization, number of operations), storage utilization parameters (e.g., storage volume), input/output (TO) parameters (e.g., throughput, TO operations per second (TOPS), latency), message queue depth (e.g., number of messages in message queues waiting to be delivered), channel agent values and channel connection agent values, as well as specific MOM provider parameters.

The failure prediction engine **130**, more particularly, the anomaly prediction layer **132** of the machine learning layer **131**, analyzes the collected parameters using one or more machine learning algorithms, and predicts, based at least in part on the analyzing, one or more anomalies in one or more of the MOM clusters **103**. The anomaly prediction layer **132** leverages an unsupervised learning approach and machine learning models to detect anomalies in the MOM clusters **103** to accurately predict outages. By predicting a potential outage before it occurs, the anomaly prediction layer **132** provides a basis for a decision to migrate messages to a different cluster, thus proactively eliminating the effects of an outage prior to a failure and enabling correction of problems in messaging systems without any service interruptions.

The anomaly prediction layer **132** analyzes the system parameters to identify abnormal patterns in the data to determine outliers. For example, based on historical system parameter data, the training layer **133** trains the machine learning model to identify what constitutes normal operational parameters in MOM clusters **103**. The historical parameter data comprises, for example, the same or similar attributes to those found in the collected system parameter data, such as, for example, infrastructure parameters like CPU utilization, storage utilization and TO parameters, as well as messaging platform parameters such as queue depth, channel agent values, channel connection agent values and specific MOM provider parameters (e.g., Kafka® specific parameters). Deviations from normal operations are considered anomalies by the anomaly prediction layer **132**.

Referring to the operational flow **200** in FIG. **2**, MOM cluster parameters **203** collected by, for example, a parameter data collection layer (e.g., parameter data collection layer **121**) are input to the failure prediction engine **230**, which is the same or similar to the failure prediction engine **130**. The failure prediction engine **230** illustrates a preprocessing component **235**, which processes the incoming MOM cluster parameters and the historical MOM parameter data **236** for analysis by the machine learning layer (ML) **231**. For example, the pre-processing component **235** removes any unwanted characters, punctuation, and stop words. As can be seen in FIG. **2**, the failure prediction engine **230** analyzes the incoming MOM cluster parameters **203** using an ML layer **231** comprising anomaly prediction and training layers **232** and **233**. The ML layer **231** is the same or similar to machine learning layer **131**. Based on the analysis, the anomaly prediction layer **232** generates one or more predicted anomalies (e.g., predicted anomaly **238-1**, **238-2** and/or **238-3**). Although three predicted anomalies **238-1** to **238-3** are shown in FIG. **2**, the embodiments are not necessarily limited thereto, and more or less predicted anomalies can be generated based on incoming MOM cluster parameters **203**.

The ML layer **231** leverages unsupervised learning methodology for outlier detection of the behavior of the MOM clusters **103**. In an embodiment, the machine learning layer **231** (or **131**) implements multivariate anomaly detection using an isolation forest algorithm, which does not require labeled training data. The isolation forest algorithm has the capacity to scale up to handle extremely large data sizes (e.g., terabytes) and high-dimensional problems with a large number of attributes, some of which may be irrelevant and potential noise. The isolation forest algorithm has relatively low linear time complexity and addresses masking and swamping effects in anomaly detection.

In illustrative embodiments, the machine learning model used by the ML layer **231** (or **131**) isolates an anomaly by creating decision trees over random attributes. This random partitioning produces significantly shorter paths since fewer instances of anomalies result in smaller partitions, and distinguishable attribute values are more likely to be separated in early partitioning. As a result, when a group (e.g., forest) of random trees collectively produces shorter path lengths for some particular points, then they are highly likely to be anomalies. A larger number of splits are required to isolate a normal point while an anomaly can be isolated by a shorter number of splits. For example, referring to the plots **301** and **302** in FIGS. **3**A and **3**B, a normal state point is isolated with 10 splits and an anomalous state point is isolated with four splits. The splits are shown as horizontal and vertical lines in the plot of points. The number of splits determine the level at which the isolation occurred and is used by the anomaly prediction layer **232** (or **132**) to generate an anomaly score. The process is repeated multiple number of times and the isolation level of each point is noted. Once an iteration is completed, the anomaly score of each point/instance suggests the likeliness of an anomaly. The score is a function of the average level at which the point is isolated. The top points/instances having an anomaly score exceeding a threshold are labeled as anomalies by the anomaly prediction layer **232** (or **132**). Alternatively, the ML layer **231** (or **131**) uses supervised learning models such as, for example, neural networks.

In illustrative embodiments, the parameter data collection layer **121** periodically collects MOM system parameters, including infrastructure resource values of MOM clusters **103** and inputs the collected parameters to the failure prediction engine **130** (or **230**) to perform anomaly prediction. The machine learning model (e.g., isolation forest model) is trained using historical parameter data (e.g., historical MOM parameter data **236**). If the anomaly prediction layer **132** (or **232**) identifies parameter values deviating from typical values and having an anomaly score exceeding a threshold, the anomaly prediction layer **132** (or **232**) identifies one or more anomalies associated with one or more MOM clusters (e.g., predicted anomalies **238-1**, **238-2** and/or **238-3**). FIG. **4** depicts example pseudocode **400** for anomaly prediction.

As further depicted in FIG. **2**, an identified anomaly can automatically trigger synchronization and message operation migration to a new cluster or be sent as a notification to an administrator device ("Admin device") **205** for an administrator or some other user to authorize synchronization and message operation migration prior to its commencement. For example, referring to FIG. **1**, a notification layer **134** of the failure prediction engine **130** issues an alert or other type of notification to be sent to an Admin device **105** informing an administrator or other user of the identified anomaly and the details thereof so that the administrator or other member of a human operational team can approve cluster synchronization and transfer of messaging operations from a first cluster to a second cluster prior to its execution. Alternatively, cluster synchronization and message operation migration is automatically performed following identification of an anomaly by the failure prediction engine **130** (or **230**). Whether approval is required before execution of cluster synchronization and transfer of messaging operations may depend on whether the accuracy of the machine learning model in terms of anomaly detection exceeds a given threshold, such that a more accurate machine learning model will not require authorization or analysis by human actors prior to performing cluster synchronization and message operation transfer.

Given authorization to proceed with or automatic performance of cluster synchronization and message operation transfer, the message metadata collection layer **122** of the data collection engine **120** collects message metadata from the MOM cluster **103** having the predicted anomaly. The synchronization engine **140** (or **240**) performs the tasks required to transfer messaging operations from a MOM cluster that is predicted to fail to a fail-over cluster so that transactional integrity, continued message delivery and quality of service are maintained. The metadata synchronization layer **141** of the synchronization engine **140** synchronizes message metadata between clusters following prediction of an anomaly in a given one of the MOM clusters.

Referring, for example, to the operational flow **500** in FIG. **5**, a cluster synchronization platform **510** synchronizes MOM clusters **503-1** and **503-2** for a MOM client **502**. The cluster synchronization platform **510**, MOM clusters **503-1** and **503-2**, and MOM client **502** are the same or similar to the cluster synchronization platform **110**, MOM clusters **103** and MOM clients **102** in FIG. **1**. The cluster synchronization platform **110/510** provides MOM clients **102/502** with active-active scalable MOM clusters **103/503** to seamlessly failover and migrate to without concerns about message duplicity and re-connectivity. The metadata synchronization layer **141** synchronizes message metadata (e.g., metadata **506-1** and **506-2**) of respective ones of the MOM clusters **103** (e.g., MOM clusters **503-1** and **503-2**). As noted herein, the message metadata includes, for example, details of message processing such as, but not necessarily limited to, message offset information, last message read information, last message committed information, timestamps, topic attributes, transaction identifiers, details about the protocols, interfaces and channels being used to deliver the messages, and details of the MOM clients **102**/**502**.

Referring to FIG. **5**, a metadata synchronization layer of the cluster synchronization platform **510** analyzes the metadata **506-1** and **506-2** of the MOM clusters **503-1** and **503-2** and broadcasts the updated metadata to the failover cluster **503-2** to update the failover cluster **503-2** with the message metadata **506-1** from the cluster **503-1** predicted to fail. The message metadata **506-1** comprises up to date message operation details which are provided to the failover cluster **503-2** so that messaging operations may seamlessly continue via the failover cluster **503-2** without duplication and with consistent QoS. Referring back to FIG. **1**, in some embodiments, message operations may be transferred to more than one of the MOM clusters **103** from a cluster predicted to fail, in which case, the metadata synchronization layer **141** broadcasts the metadata of a cluster predicted to fail to multiple ones of the MOM clusters **103**. Additionally, in some embodiments, more than one of the MOM clusters **103** may be predicted to fail, in which case their corresponding metadata is collected and synchronized with one or more of the remaining MOM clusters **103** to be used as failover clusters.

According to an embodiment, in the synchronization process, the metadata synchronization layer **141** compares the message metadata from one of the MOM clusters **103** with an identified anomaly with message metadata from one or more remaining ones the MOM clusters **103** to be used as a failover cluster(s) to determine differences between the message metadata from the MOM cluster predicted to fail and the message metadata from the one or more remaining ones of the MOM clusters **103** to be used as a failover cluster(s). The metadata synchronization layer **141** determines, based at least in part on the determined differences, at least a portion of the message metadata from the one or more remaining ones of the MOM clusters **103** requiring an update. Based on what message metadata is required to update the remaining ones of the MOM clusters **103** taking over messaging operations, at least part of the message metadata from the MOM cluster predicted to fail is transmitted to the one or more remaining ones of the MOM clusters **103** to be used as a failover cluster(s). In other words, the metadata synchronization layer **141** analyzes the message metadata of the cluster predicted to fail and of the failover cluster(s) to ensure that the failover cluster(s) have the required metadata reflecting up to date messaging operations. In this way, the failover cluster(s) can continue messaging operations from where they left off in the cluster predicted to fail. Any metadata determined to be lacking in the failover cluster(s) and required to complete the continuous processing of messages is transmitted from the cluster predicted to fail to the failover cluster(s). In some instances, if the primary cluster and failover cluster utilize different MOM system formats (e.g., IBM® MQ vs. Kafka®), the metadata synchronization layer **141** translates the message metadata from a format of a first MOM system to a format of a second MOM system.

Referring, for example, to FIG. **6**, a class diagram **600** for implementing cluster synchronization includes a cluster

synchronization base class **650**, which is triggered once the cluster synchronization services are started. The cluster synchronization base class **650** comprises a controller service which manages a plurality of interfaces between the cluster synchronization platform, the MOM clients **102**, the MOM clusters **103** and the administrator devices **105**. A plurality of MOM source classes **651-1**, **651-2** and **651-3** (collectively "MOM source classes **651**") and a plurality of MOM destination classes **652-1**, **652-2** and **652-3** (collectively "MOM destination classes **652**") are shown. The source classes **651** are end points which connect to respective source MOM metadata stores of MOM clusters **103**, and the destination classes **652** are endpoints which connect to respective destination MOM metadata stores of MOM clusters **103**. Source metadata stores correspond to metadata stores of MOM clusters **103** predicted to fail and destination metadata stores correspond to metadata stores of failover MOM clusters **103**.

A plurality of publisher classes **658-1**, **658-2** and **658-3** (collectively "publisher classes **658**") and a plurality of listener classes **655-1**, **655-2** and **655-3** (collectively "listener classes **655**") are shown. The publisher classes **658** publish metadata change events to the metadata stores of the MOM clusters **103**, which may correspond to particular MOM systems such as, for example, Kafka® topics, MQ queues and/or database (DB) queues. The listener classes **655** consume the metadata change events from metadata stores of the MOM clusters **103**.

A plurality of updater classes **657-1**, **657-2** and **657-3** (collectively "updater classes **657**") update the metadata on the destination metadata stores of, for example, the MOM clusters **103** which are failover clusters so that the failover clusters can continue messaging operations from where they left off in the clusters predicted to fail as described herein. A plurality of comparator classes **654-1**, **654-2** and **654-3** (collectively "comparator classes **654**") compare the incoming metadata with the destination metadata as described herein and trigger any updates required at destination metadata stores using the updater classes **657**. A plurality of translator classes **656-1**, **656-2** and **656-3** (collectively "translator classes **656**") translate metadata from one MOM system format to another MOM system format as described herein (e.g., IBM® MQ "Message ID" to Kafka® topic "Record Offset").

Although three of each class **651**, **652**, **654**, **655**, **656**, **657** and **658** are shown in FIG. **6**, the embodiments are not necessarily limited thereto, and more or less classes can be used. The number of classes are varied based on, for example, the different MOM products. For example, the classes −1, −2 and −3 may respectively correspond to IBM® MQ, RabbitMQ® and Kafka® MOM products.

A core API **653** provides one or more APIs to MOM clients **102**. The one or more APIs are used by the MOM clients **102** to update or get updated metadata to use while switching between clusters **103** or different MOM products. In accordance with an embodiment, if a global traffic manager (GTM) or local traffic manager (LTM) fails to switch due to F5 errors, then a MOMSwitch Java class is triggered automatically to provide a method for MOM client applications to switch and automatically resume processing in case of fail-over between active and standby MOM servers.

The cluster migration layer **142** of the cluster synchronization engine **140** controls the migrations or transfer of messaging operations from a MOM cluster predicted to fail to the one or more remaining ones of the MOM clusters **103** to serve as failover clusters. The cluster migration layer **142**, for example, comprises the controller service managing the interfaces between the cluster synchronization platform **110**, the MOM clients **102**, the MOM clusters **103** and the administrator devices **105**. The cluster migration layer **142**, for example, manages the distribution of the APIs used by the MOM clients **102** to update or get updated metadata to use while switching between clusters **103** or different MOM products. In illustrative embodiments, the cluster migration layer **142** enables active-active scalable MOM clusters **103** for MOM clients **102** to seamlessly failover and migrate different MOM platforms (e.g., Kafka®/RabbitMQ®/IBM® MQ) without concerns about message duplicity and reconnectivity as described herein with, for example, 2-phase commit XA protocol coordination. FIG. **7** depicts example pseudocode **700** for cluster migration.

According to an embodiment, the cluster synchronization platform **110** is compatible with the vendor specific software, commands, formats and data of different MOM platforms to which it is connected. The data collection engine **120** retrieves vendor specific data and metadata from MOM servers to which the cluster synchronization platform **110** is connected. The vendor specific data and metadata are in a native command format of the corresponding MOM servers and/or MOM clusters **103** from which the vendor specific data and metadata are retrieved. The data collection engine **120** retrieves data in the native command format of each MOM server.

In addition to the message metadata described hereinabove, the message metadata further includes, for example, messaging queue names, messaging queue statuses (e.g., online, offline, idle, active), messaging queue locations (e.g., Internet Protocol (IP) addresses, ports), messaging queue types, timestamps for messages entering and leaving message queues, transmission times of messages from messaging queues, connections between messaging queues and of messaging queues to message producers and message consumers, total number of messages, and/or message transmission rates.

According to one or more embodiments, the metadata store **106-1** and other data stores or databases referred to herein can be configured according to a relational database management system (RDBMS) (e.g., PostgreSQL). In some embodiments, the metadata store **106-1** and other data stores or databases referred to herein are implemented using one or more storage systems or devices associated with the cluster synchronization platform **110**. In some embodiments, one or more of the storage systems utilized to implement the metadata store **106-1** and other data stores or databases referred to herein comprise a scale-out all-flash content addressable storage array or other type of storage array.

The term "storage system" as used herein is therefore intended to be broadly construed, and should not be viewed as being limited to content addressable storage systems or flash-based storage systems. A given storage system as the term is broadly used herein can comprise, for example, network-attached storage (NAS), storage area networks (SANs), direct-attached storage (DAS) and distributed DAS, as well as combinations of these and other storage types, including software-defined storage.

Other particular types of storage products that can be used in implementing storage systems in illustrative embodiments include all-flash and hybrid flash storage arrays, software-defined storage products, cloud storage products, object-based storage products, and scale-out NAS clusters. Combinations of multiple ones of these and other storage products can also be used in implementing a given storage system in an illustrative embodiment.

Although shown as elements of the cluster synchronization platform **110**, the data collection engine **120**, failure prediction engine **130** and/or synchronization engine **140** in other embodiments can be implemented at least in part externally to the cluster synchronization platform **110**, for example, as stand-alone servers, sets of servers or other types of systems coupled to the network **104**. For example, the data collection engine **120**, failure prediction engine **130** and/or synchronization engine **140** may be provided as cloud services accessible by the cluster synchronization platform **110**.

The data collection engine **120**, failure prediction engine **130** and/or synchronization engine **140** in the FIG. **1** embodiment are each assumed to be implemented using at least one processing device. Each such processing device generally comprises at least one processor and an associated memory, and implements one or more functional modules for controlling certain features of the data collection engine **120**, failure prediction engine **130** and/or synchronization engine **140**.

At least portions of the cluster synchronization platform **110** and the elements thereof may be implemented at least in part in the form of software that is stored in memory and executed by a processor. The cluster synchronization platform **110** and the elements thereof comprise further hardware and software required for running the cluster synchronization platform **110**, including, but not necessarily limited to, on-premises or cloud-based centralized hardware, graphics processing unit (GPU) hardware, virtualization infrastructure software and hardware, Docker containers, networking software and hardware, and cloud infrastructure software and hardware.

Although the data collection engine **120**, failure prediction engine **130**, synchronization engine **140** and other elements of the cluster synchronization platform **110** in the present embodiment are shown as part of the cluster synchronization platform **110**, at least a portion of the data collection engine **120**, failure prediction engine **130**, synchronization engine **140** and other elements of the cluster synchronization platform **110** in other embodiments may be implemented on one or more other processing platforms that are accessible to the cluster synchronization platform **110** over one or more networks. Such elements can each be implemented at least in part within another system element or at least in part utilizing one or more stand-alone elements coupled to the network **104**.

It is assumed that the cluster synchronization platform **110** in the FIG. **1** embodiment and other processing platforms referred to herein are each implemented using a plurality of processing devices each having a processor coupled to a memory. Such processing devices can illustratively include particular arrangements of compute, storage and network resources. For example, processing devices in some embodiments are implemented at least in part utilizing virtual resources such as virtual machines (VMs) or Linux containers (LXCs), or combinations of both as in an arrangement in which Docker containers or other types of LXCs are configured to run on VMs.

The term "processing platform" as used herein is intended to be broadly construed so as to encompass, by way of illustration and without limitation, multiple sets of processing devices and one or more associated storage systems that are configured to communicate over one or more networks.

As a more particular example, the data collection engine **120**, failure prediction engine **130**, synchronization engine **140** and other elements of the cluster synchronization platform **110**, and the elements thereof can each be implemented in the form of one or more LXCs running on one or more VMs. Other arrangements of one or more processing devices of a processing platform can be used to implement the data collection engine **120**, failure prediction engine **130** and synchronization engine **140**, as well as other elements of the cluster synchronization platform **110**. Other portions of the system **100** can similarly be implemented using one or more processing devices of at least one processing platform.

Distributed implementations of the system **100** are possible, in which certain elements of the system reside in one data center in a first geographic location while other elements of the system reside in one or more other data centers in one or more other geographic locations that are potentially remote from the first geographic location. Thus, it is possible in some implementations of the system **100** for different portions of the cluster synchronization platform **110** to reside in different data centers. Numerous other distributed implementations of the cluster synchronization platform **110** are possible.

Accordingly, one or each of the data collection engine **120**, failure prediction engine **130**, synchronization engine **140** and other elements of the cluster synchronization platform **110** can each be implemented in a distributed manner so as to comprise a plurality of distributed elements implemented on respective ones of a plurality of compute nodes of the cluster synchronization platform **110**.

It is to be appreciated that these and other features of illustrative embodiments are presented by way of example only, and should not be construed as limiting in any way. Accordingly, different numbers, types and arrangements of system elements such as the data collection engine **120**, failure prediction engine **130**, synchronization engine **140** and other elements of the cluster synchronization platform **110**, and the portions thereof can be used in other embodiments.

It should be understood that the particular sets of modules and other elements implemented in the system **100** as illustrated in FIG. **1** are presented by way of example only. In other embodiments, only subsets of these elements, or additional or alternative sets of elements, may be used, and such elements may exhibit alternative functionality and configurations.

For example, as indicated previously, in some illustrative embodiments, functionality for the cluster synchronization platform can be offered to cloud infrastructure customers or other users as part of FaaS, CaaS and/or PaaS offerings.

The operation of the information processing system **100** will now be described in further detail with reference to the flow diagram of FIG. **8**. With reference to FIG. **8**, a process **800** for cluster synchronization as shown includes steps **802** through **810**, and is suitable for use in the system **100** but is more generally applicable to other types of information processing systems comprising a cluster synchronization platform configured for synchronizing MOM clusters.

In step **802**, MOM system parameters are collected from a plurality of MOM clusters. The plurality of MOM clusters respectively comprise a plurality of nodes. The MOM system parameters comprise at least one of one or more central processing unit utilization parameters, one or more storage utilization parameters, one or more input/output parameters, message queue depth, one or more channel agent values and one or more channel connection agent values.

In step **804**, the parameters are analyzed using one or more machine learning algorithms. The one or more machine learning algorithms utilize an unsupervised learning technique to detect one or more outlier parameters of the parameters, and comprise, for example, an isolation forest algorithm. In an embodiment, the one or more machine learning algorithms are trained with training data comprising historical parameter data.

In step **806**, based at least in part on the analyzing, at least one anomaly in a MOM cluster of the plurality of MOM clusters is predicted, and in step **808**, message metadata is collected from the MOM cluster where the at least one anomaly is predicted. The message metadata comprises at least one of message offset information, last message read information, last message committed information, one or more timestamps, one or more topic attributes and one or more transaction identifiers.

In step **810**, at least part of the message metadata is transmitted to one or more remaining ones of the plurality of MOM clusters. The part of the message metadata corresponds to messaging operations to be transferred from the MOM cluster where the at least one anomaly is predicted to the one or more remaining ones of the plurality of MOM clusters.

According to an embodiment, the collecting of the message metadata and the transmitting of at least the part of the message metadata is performed in response to the predicting of the at least one anomaly in the MOM cluster.

In one or more embodiments, the message metadata from the MOM cluster where the at least one anomaly is predicted is compared with message metadata from the one or more remaining ones of the plurality of MOM clusters to determine differences between the message metadata from the MOM cluster where the at least one anomaly is predicted and the message metadata from the one or more remaining ones of the plurality of MOM clusters. Based at least in part on the differences, at least a portion of the message metadata from the one or more remaining ones of the plurality of MOM clusters requiring an update is determined. The part of the message metadata transmitted to the one or more remaining ones of the plurality of MOM clusters corresponds to the message metadata from the one or more remaining ones of the plurality of MOM clusters requiring the update.

In an embodiment, the method further comprises translating the message metadata from a format of a first MOM system to a format of a second MOM system. One or more APIs are provided to one or more MOM clients. The one or more APIs are used by the one or more MOM clients to retrieve at least the part of the message metadata.

It is to be appreciated that the FIG. **8** process and other features and functionality described above can be adapted for use with other types of information systems configured to execute cluster synchronization services in a cluster synchronization platform or other type of platform.

The particular processing operations and other system functionality described in conjunction with the flow diagram of FIG. **8** are therefore presented by way of illustrative example only, and should not be construed as limiting the scope of the disclosure in any way. Alternative embodiments can use other types of processing operations. For example, the ordering of the process steps may be varied in other embodiments, or certain steps may be performed at least in part concurrently with one another rather than serially. Also, one or more of the process steps may be repeated periodically, or multiple instances of the process can be performed in parallel with one another.

Functionality such as that described in conjunction with the flow diagram of FIG. **8** can be implemented at least in part in the form of one or more software programs stored in memory and executed by a processor of a processing device such as a computer or server. As will be described below, a memory or other storage device having executable program code of one or more software programs embodied therein is an example of what is more generally referred to herein as a "processor-readable storage medium."

Illustrative embodiments of systems with a cluster synchronization platform as disclosed herein can provide a number of significant advantages relative to conventional arrangements. For example, the cluster synchronization platform uses machine learning to proactively predict middleware outages to minimize impact on message delivery. The embodiments advantageously leverage an unsupervised learning approach and machine learning models to detect anomalies in MOM clusters and accurately predict outages. By predicting an upcoming outage before it occurs, the embodiments facilitate decision-making for migration of messaging operations to different clusters and eliminate the effects of outages by addressing them prior to their actual occurrence.

As an additional advantage, the embodiments synchronize MOM clusters for MOM client applications to avoid message duplicity and re-connectivity issues when switching operations between different clusters. A cluster synchronization platform synchronizes message metadata between MOM clusters. The synchronization process includes metadata analysis and comparison between clusters and broadcasting of updated metadata to failover clusters.

The embodiments provide for seamless failover of MOM systems, regardless of their type. Outages are predicted using advanced anomaly detection based on MOM system parameter values. Responsive to a predicted outage, the embodiments manage migration of messaging operations from a primary MOM cluster to a failover cluster/server, while maintaining transactional integrity, message delivery guarantees and QoS. The embodiments include techniques for synchronizing metadata between clusters.

By leveraging machine learning for anomaly detection, the embodiments monitor various system parameters including, for example, MOM system metrics. By measuring normal parameter values, the machine learning model detects anomalies when parameter values deviate from normal values. Based on identification of an anomaly, a decision can be made to switch to a secondary cluster before an outage of the primary cluster occurs. While the issues in the primary cluster are investigated, messages can flow through the secondary cluster uninterrupted, maintaining continuity.

The embodiments advantageously allow failover between differently configured MOM providers, where messaging operations are continued from where they left off prior to transfer to a different cluster without duplicity and rework. The embodiments eliminate the need for duplicate message handling and reconnection logic, saving development, integration testing and unit testing resources. The embodiments further provide active-active scalable MOM clusters offering seamless failover and faster migrations in the event of system problems.

It is to be appreciated that the particular advantages described above and elsewhere herein are associated with particular illustrative embodiments and need not be present in other embodiments. Also, the particular types of information processing system features and functionality as illustrated in the drawings and described above are exemplary only, and numerous other arrangements may be used in other embodiments.

As noted above, at least portions of the information processing system **100** may be implemented using one or more processing platforms. A given such processing platform comprises at least one processing device comprising a processor coupled to a memory. The processor and memory in some embodiments comprise respective processor and memory elements of a virtual machine or container provided using one or more underlying physical machines. The term "processing device" as used herein is intended to be broadly construed so as to encompass a wide variety of different arrangements of physical processors, memories and other device components as well as virtual instances of such components. For example, a "processing device" in some embodiments can comprise or be executed across one or more virtual processors. Processing devices can therefore be physical or virtual and can be executed across one or more physical or virtual processors. It should also be noted that a given virtual device can be mapped to a portion of a physical one.

Some illustrative embodiments of a processing platform that may be used to implement at least a portion of an information processing system comprise cloud infrastructure including virtual machines and/or container sets implemented using a virtualization infrastructure that runs on a physical infrastructure. The cloud infrastructure further comprises sets of applications running on respective ones of the virtual machines and/or container sets.

These and other types of cloud infrastructure can be used to provide what is also referred to herein as a multi-tenant environment. One or more system elements such as the cluster synchronization platform **110** or portions thereof are illustratively implemented for use by tenants of such a multi-tenant environment.

As mentioned previously, cloud infrastructure as disclosed herein can include cloud-based systems. Virtual machines provided in such systems can be used to implement at least portions of one or more of a computer system and a cluster synchronization platform in illustrative embodiments. These and other cloud-based systems in illustrative embodiments can include object stores.

Illustrative embodiments of processing platforms will now be described in greater detail with reference to FIGS. **9** and **10**. Although described in the context of system **100**, these platforms may also be used to implement at least portions of other information processing systems in other embodiments.

FIG. **9** shows an example processing platform comprising cloud infrastructure **900**. The cloud infrastructure **900** comprises a combination of physical and virtual processing resources that may be utilized to implement at least a portion of the information processing system **100**. The cloud infrastructure **900** comprises multiple virtual machines (VMs) and/or container sets **902-1**, **902-2**, . . . **902**-L implemented using virtualization infrastructure **904**. The virtualization infrastructure **904** runs on physical infrastructure **905**, and illustratively comprises one or more hypervisors and/or operating system level virtualization infrastructure. The operating system level virtualization infrastructure illustratively comprises kernel control groups of a Linux operating system or other type of operating system.

The cloud infrastructure **900** further comprises sets of applications **910-1**, **910-2**, . . . **910**-L running on respective ones of the VMs/container sets **902-1**, **902-2**, . . . **902**-L under the control of the virtualization infrastructure **904**. The VMs/container sets **902** may comprise respective VMs, respective sets of one or more containers, or respective sets of one or more containers running in VMs.

In some implementations of the FIG. **9** embodiment, the VMs/container sets **902** comprise respective VMs implemented using virtualization infrastructure **904** that comprises at least one hypervisor. A hypervisor platform may be used to implement a hypervisor within the virtualization infrastructure **904**, where the hypervisor platform has an associated virtual infrastructure management system. The underlying physical machines may comprise one or more distributed processing platforms that include one or more storage systems.

In other implementations of the FIG. **9** embodiment, the VMs/container sets **902** comprise respective containers implemented using virtualization infrastructure **904** that provides operating system level virtualization functionality, such as support for Docker containers running on bare metal hosts, or Docker containers running on VMs. The containers are illustratively implemented using respective kernel control groups of the operating system.

As is apparent from the above, one or more of the processing modules or other components of system **100** may each run on a computer, server, storage device or other processing platform element. A given such element may be viewed as an example of what is more generally referred to herein as a "processing device." The cloud infrastructure **900** shown in FIG. **9** may represent at least a portion of one processing platform. Another example of such a processing platform is processing platform **1000** shown in FIG. **10**.

The processing platform **1000** in this embodiment comprises a portion of system **100** and includes a plurality of processing devices, denoted **1002-1**, **1002-2**, **1002-3**, . . . **1002**-K, which communicate with one another over a network **1004**.

The network **1004** may comprise any type of network, including by way of example a global computer network such as the Internet, a WAN, a LAN, a satellite network, a telephone or cable network, a cellular network, a wireless network such as a WiFi or WiMAX network, or various portions or combinations of these and other types of networks.

The processing device **1002-1** in the processing platform **1000** comprises a processor **1010** coupled to a memory **1012**. The processor **1010** may comprise a microprocessor, a microcontroller, an application-specific integrated circuit (ASIC), a field-programmable gate array (FPGA), a central processing unit (CPU), a graphical processing unit (GPU), a tensor processing unit (TPU), a video processing unit (VPU) or other type of processing circuitry, as well as portions or combinations of such circuitry elements.

The memory **1012** may comprise random access memory (RAM), read-only memory (ROM), flash memory or other types of memory, in any combination. The memory **1012** and other memories disclosed herein should be viewed as illustrative examples of what are more generally referred to as "processor-readable storage media" storing executable program code of one or more software programs.

Articles of manufacture comprising such processor-readable storage media are considered illustrative embodiments. A given such article of manufacture may comprise, for example, a storage array, a storage disk or an integrated circuit containing RAM, ROM, flash memory or other electronic memory, or any of a wide variety of other types of computer program products. The term "article of manufacture" as used herein should be understood to exclude transitory, propagating signals. Numerous other types of computer program products comprising processor-readable storage media can be used.

Also included in the processing device **1002-1** is network interface circuitry **1014**, which is used to interface the processing device with the network **1004** and other system components, and may comprise conventional transceivers.

The other processing devices **1002** of the processing platform **1000** are assumed to be configured in a manner similar to that shown for processing device **1002-1** in the figure.

Again, the particular processing platform **1000** shown in the figure is presented by way of example only, and system **100** may include additional or alternative processing platforms, as well as numerous distinct processing platforms in any combination, with each such platform comprising one or more computers, servers, storage devices or other processing devices.

For example, other processing platforms used to implement illustrative embodiments can comprise converged infrastructure.

It should therefore be understood that in other embodiments different arrangements of additional or alternative elements may be used. At least a subset of these elements may be collectively implemented on a common processing platform, or each such element may be implemented on a separate processing platform.

As indicated previously, components of an information processing system as disclosed herein can be implemented at least in part in the form of one or more software programs stored in memory and executed by a processor of a processing device. For example, at least portions of the functionality of one or more elements of the cluster synchronization platform **110** as disclosed herein are illustratively implemented in the form of software running on one or more processing devices.

It should again be emphasized that the above-described embodiments are presented for purposes of illustration only. Many variations and other alternative embodiments may be used. For example, the disclosed techniques are applicable to a wide variety of other types of information processing systems and cluster synchronization platforms. Also, the particular configurations of system and device elements and associated processing operations illustratively shown in the drawings can be varied in other embodiments. Moreover, the various assumptions made above in the course of describing the illustrative embodiments should also be viewed as exemplary rather than as requirements or limitations of the disclosure. Numerous other alternative embodiments within the scope of the appended claims will be readily apparent to those skilled in the art.

What is claimed is:

1. A method, comprising:

collecting message-oriented-middleware system parameters from a plurality of message-oriented-middleware clusters;

analyzing the message-oriented-middleware system parameters using one or more machine learning algorithms;

predicting, based at least in part on the analyzing, at least one anomaly in a message-oriented-middleware cluster of the plurality of message-oriented-middleware clusters;

collecting message metadata from the message-oriented-middleware cluster based, at least in part, on the predicting;

transmitting at least part of the message metadata to one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein the part of the message metadata corresponds to messaging operations to be transferred from the message-oriented-middleware cluster to the one or more remaining ones of the plurality of message-oriented-middleware clusters, and wherein the part of the message metadata comprises one or more details about progress of message transmission in the message-oriented-middleware cluster, the one or more details including at least one of message offset information and one or more timestamps for messages committed to transmission by the message-oriented-middleware cluster; and

synchronizing, based at least in part on the one or more details about the progress of the message transmission, the messaging operations between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters to prevent message duplication between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein the synchronizing comprises translating the message metadata from a format of a first message-oriented-middleware system to a format of a second message-oriented-middleware system to permit the second message-oriented-middleware system to process the one or more details about the progress of the message transmission and prevent re-transmission of the messages committed to transmission by the message-oriented-middleware cluster; and

wherein the steps of the method are executed by a processing device operatively coupled to a memory.

2. The method of claim **1**, wherein the plurality of message-oriented-middleware clusters respectively comprise a plurality of nodes.

3. The method of claim **1**, wherein the message-oriented-middleware system parameters comprise at least one of one or more central processing unit utilization parameters, one or more storage utilization parameters, one or more input/output parameters, message queue depth, one or more channel agent values and one or more channel connection agent values.

4. The method of claim **1**, wherein the part of the message metadata further comprises at least one of last message read information, last message committed information, one or more topic attributes and one or more transaction identifiers.

5. The method of claim **1**, wherein the one or more machine learning algorithms utilize an unsupervised learning technique to detect one or more outlier parameters of the message-oriented-middleware system parameters.

6. The method of claim **5**, wherein the one or more machine learning algorithms comprise an isolation forest algorithm.

7. The method of claim **6**, further comprising training the one or more machine learning algorithms with training data comprising historical parameter data.

8. The method of claim **1**, wherein the collecting of the message metadata and the transmitting of at least the part of the message metadata is performed in response to the predicting of the at least one anomaly in the message-oriented-middleware cluster.

9. The method of claim **1**, further comprising comparing the message metadata from the message-oriented-middleware cluster with message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters to determine differences between the message metadata from the message-oriented-middleware cluster and the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters.

10. The method of claim **9**, further comprising determining, based at least in part on the differences, at least a portion

of the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters requiring an update.

11. The method of claim **10**, wherein the part of the message metadata transmitted to the one or more remaining ones of the plurality of message-oriented-middleware clusters corresponds to the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters requiring the update.

12. The method of claim **1**, further comprising providing one or more application programming interfaces to one or more message-oriented-middleware clients, wherein the one or more application programming interfaces are used by the one or more message-oriented-middleware clients to retrieve at least the part of the message metadata.

13. An apparatus comprising:

a processing device operatively coupled to a memory and configured to:

collect message-oriented-middleware system parameters from a plurality of message-oriented-middleware clusters;

analyze the message-oriented-middleware system parameters using one or more machine learning algorithms;

predict, based at least in part on the analyzing, at least one anomaly in a message-oriented-middleware cluster of the plurality of message-oriented-middleware clusters;

collect message metadata from the message-oriented-middleware cluster based, at least in part, on the predicting;

transmit at least part of the message metadata to one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein the part of the message metadata corresponds to messaging operations to be transferred from the message-oriented-middleware cluster to the one or more remaining ones of the plurality of message-oriented-middleware clusters, and wherein the part of the message metadata comprises one or more details about progress of message transmission in the message-oriented-middleware cluster, the one or more details including at least one of message offset information and one or more timestamps for messages committed to transmission by the message-oriented-middleware cluster; and

synchronize, based at least in part on the one or more details about the progress of the message transmission, the messaging operations between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters to prevent message duplication between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein, in synchronizing, the processing device is configured to translate the message metadata from a format of a first message-oriented-middleware system to a format of a second message-oriented-middleware system to permit the second message-oriented-middleware system to process the one or more details about the progress of the message transmission and prevent re-transmission of the messages committed to transmission by the message-oriented-middleware cluster.

14. The apparatus of claim **13**, wherein the plurality of message-oriented-middleware clusters respectively comprise a plurality of nodes.

15. The apparatus of claim **13**, wherein the processing device is further configured to compare the message metadata from the message-oriented-middleware cluster with message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters to determine differences between the message metadata from the message-oriented-middleware cluster and the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters.

16. The apparatus of claim **15**, wherein the processing device is further configured to determine, based at least in part on the differences, at least a portion of the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters requiring an update.

17. An article of manufacture comprising a non-transitory processor-readable storage medium having stored therein program code of one or more software programs, wherein the program code when executed by at least one processing device causes said at least one processing device to perform the steps of:

collecting message-oriented-middleware system parameters from a plurality of message-oriented-middleware clusters;

analyzing the message-oriented-middleware system parameters using one or more machine learning algorithms;

predicting, based at least in part on the analyzing, at least one anomaly in a message-oriented-middleware cluster of the plurality of message-oriented-middleware clusters;

collecting message metadata from the message-oriented-middleware cluster based, at least in part, on the predicting;

transmitting at least part of the message metadata to one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein the part of the message metadata corresponds to messaging operations to be transferred from the message-oriented-middleware cluster to the one or more remaining ones of the plurality of message-oriented-middleware clusters, and wherein the part of the message metadata comprises one or more details about progress of message transmission in the message-oriented-middleware cluster, the one or more details including at least one of message offset information and one or more timestamps for messages committed to transmission by the message-oriented-middleware cluster; and

synchronizing, based at least in part on the one or more details about the progress of the message transmission, the messaging operations between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters to prevent message duplication between the message-oriented-middleware cluster and the one or more remaining ones of the plurality of message-oriented-middleware clusters;

wherein, in synchronizing, the program code causes said at least one processing device to translate the message metadata from a format of a first message-oriented-middleware system to a format of a second message-oriented-middleware system to permit the second message-oriented-middleware system to process the one or more details about the progress of the message transmission and prevent re-transmission of the messages committed to transmission by the message-oriented-middleware cluster.

18. The article of manufacture of claim **17**, wherein the plurality of message-oriented-middleware clusters respectively comprise a plurality of nodes.

19. The article of manufacture of claim **17**, wherein the program code causes said at least one processing device to further perform the step of comparing the message metadata from the message-oriented-middleware cluster with message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters to determine differences between the message metadata from the message-oriented-middleware cluster and the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters.

20. The article of manufacture of claim **19**, wherein the program code causes said at least one processing device to further perform the step of determining, based at least in part on the differences, at least a portion of the message metadata from the one or more remaining ones of the plurality of message-oriented-middleware clusters requiring an update.

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